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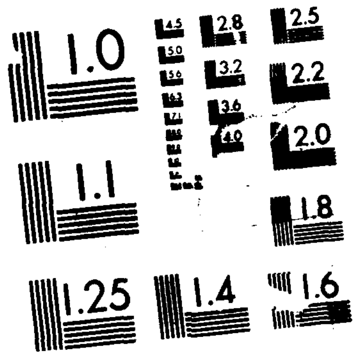

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ROBUSTNESS IN COST

PERFORMANCE MODELS

THESIS

Darren E. Morgan, B.S.
Captain, USAF

AFIT/GSM/LSY/87S-23

DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY
AIR FORCE INSTITUTE OF TECHNOLOGY

87 12 3 021

Wright-Patterson Air Force Base, Ohio

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AFIT/GSM/LSY/87S-23

ROBUSTNESS IN COST PERFORMANCE MODELS

THESIS

Presented to the Faculty of the

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Darren E. Morgan, B.S.

Captain, USAF

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Table of Contents

List of Tables

Table		Page

AFIT/GSM/LSY/87S-23

Abstract

This thesis examined the robustness of methods used to compute estimates at completion of contract costs. The four techniques examined were a subset of those used by the Cost Performance Report Analysis computer program to derive estimates at completion.

Monte Carlo simulation methods were used to generate the required data values for 18 simulated populations representing a variety of possible cost and schedule overrun scenarios. A statistical evaluation of the robustness of the four estimate at completion techniques was performed using samples from each of the 18 simulated populations.

The results of this analysis indicate that, for practical purposes, none of the selected estimate at completion techniques are robust for the cost and schedule overrun scenarios that were investigated. The tendency of each of the estimate at completion models was to underestimate the final contract cost. The estimate at completion models incorporating mathematical smoothing techniques (i.e. weightings or moving averages) provided relatively stable results across all of the populations; however, they were unable to consistently predict a contract's completion cost within 30 percent of the actual

value. Of the four methods investigated, the method based upon the Cost Performance Index for a single month was the most unreliable predictor of the final contract cost.

ROBUSTNESS IN COST PERFORMANCE MODELS

I. Introduction

General Issue

Department of Defense (DOD) Instruction 7000.2, Performance Measurement for Selected Acquisitions, established the Cost/Schedule Control Systems Criteria (C/SCSC) as a method of assessing contractor performance on major systems acquisitions (19:36). The primary objectives of C/SCSC are to ensure DOD contractors use effective internal management control systems and to provide the government with timely and auditable data for monitoring contract progress (1:45). Air Force Systems Command Pamphlet 173-5, Cost Analysis [:] Cost/Schedule Control Systems Criteria Joint Implementation Guide, identifies the minimum requirements for contractors' management control systems:

1. Realistic budgets for work scheduled within responsibility assignments (6:5).

2. Accurate accumulation of costs related to progress of the planned work (6:5).

3. Comparison between the actual resources applied and the estimated resources planned for specific work assignments (6:5).

4. Preparation of reliable estimates of costs to complete remaining work (6:5).

5. Support of an overall capability for managers to analyze available information to identify problem areas in sufficient time to take remedial action (6:5).

The C/SCSC have no explicit reporting requirements; however, summary data generated by the contractor's internal management control system are reported to the government program office through the Cost Performance Report (CPR) (1:46). A required data item is the Estimate at Completion (EAC) which is computed for each element in the Work Breakdown Structure and each major functional category within the organization (5:ii). The EAC is a "continually revised value which reflects the contractor's estimate to complete the physical requirements of the contract" (5:ii).

The EAC is an important measure of the contractor's performance and a primary input into periodic program status reports sent to the major acquisition commands, the Office of the Secretary of Defense, and the Congress (1:47). Therefore, it is particularly important to verify the methods and database used by the contractor to calculate the EAC.

Specific Problem

The Department of Defense "does not have the resources to examine the internal plans and resource allocations of the contractor; it must make its predictions [EACs] on the basis of contractor performance on work already completed" (4:2). As a result, a number of automated techniques have

been developed to generate EACs on the basis of contractor performance to date. Holeman identifies the major problem in applying these techniques; "there does not appear to have been any attempt to conduct in-depth or independent reviews of any of these automated approaches to offer unbiased and expert guidance on when and where they should or should not be used" (11:40). The choice of an appropriate technique is further complicated by the fact that several "of these techniques could be considered analytically sophisticated and many analysts in program offices would probably have difficulty in fully understanding their supporting documentation" (11:40). Consequently, analysts may apply inappropriate techniques to generate EACs believed to be accurate because they have been generated by a computer to eight decimal places; when, in actuality, they may be quite unrealistic.

This thesis evaluates the robustness of four techniques, or models, for generating EACs. Estimates can be point or interval estimates; this research is interested in the robustness of point estimates--specifically, point estimates of contract completion costs. A point estimate may be considered robust if it produces acceptable results for a variety of conditions or situations. The definition of "robust" depends on who is defining it and, thus, is necessarily subjective. For example, a point estimate of a contract's cost may be considered robust by one analyst if

it is within 10 percent of the final contract cost over a wide range of conditions; another analyst may only require the estimate to be within 30 percent of the final cost to be considered robust (14:1). A robust model would be useful because it would allow analysts to achieve adequate results over a wide range of situations.

Definition of Key Terms

The following terms are used throughout this thesis and are presented to aid the reader's understanding.

1. Actual Cost of Work Performed (ACWP). The costs actually incurred and recorded in accomplishing the work performed within a given time period (6:5).

2. Budget at Completion (BAC). The budgetary goal for total amount of work required on the contract (5:5).

3. Budgeted Cost for Work Performed (BCWP). The sum of the budgets for completed work packages and completed portions of open work packages, plus the appropriate portion of the budgets for level of effort and apportioned effort (6:6).

4. Budgeted Cost for Work Remaining (BCWR). The difference between the budgetary goal (BAC) and the sum of the budgets for work completed to date (cumulative BCWP).

5. Budgeted Cost for Work Scheduled (BCWS). The sum of the budgets for all work packages, planning packages, etc., scheduled to be accomplished (including in-process work packages), plus the amount of level of effort and apportioned effort scheduled to be accomplished within a given time period (6:6).

6. Estimated Cost at Completion or Estimate at Completion (EAC). Actual direct costs, plus indirect costs allocable to the contract, plus the estimate of costs (direct and indirect) for authorized work remaining (6:6).

7. Performance Measurement Baseline. The time-phased budget plan against which contract performance is measured. It equals the total allocated budget less management reserve (6:6).

8. Work Packages. Detailed short-span jobs, or material items, identified by the contractor for accomplishing work required to complete the contract (6:6).

Description of EAC Formulas

The EAC formulas used in this research are four of the automated methods for generating EACs employed by the Air Force Wright Aeronautical Laboratories (AFWAL) at Wright-Patterson Air Force Base, Ohio. These methods were selected for study to further the research previously accomplished by Captain James Price and documented in his thesis, An Evaluation of CPRA Estimate at Completion Techniques Based Upon AFWAL Cost/Schedule Control System Criteria Data.

Formula Convention. In the EAC formulas and several variance and index equations, it is often necessary to reference two data points with the same variable name (for example, the value of BCWP for the months of June and July). When this occurs, the following convention will be used. (This convention is similar to that used by Captain Price.) The data point will retain its variable name (i.e. "BCWP"), but an indicator of its position in the array of data points also will be attached. The last month for which data is available will have the indicator, "(CUM)," added. Preceding data points in the array will be

described with the indicator, "(CUM-n)," where "n" is the number of months prior to the last data point. An example should make this clear. If BCWP data is available for August through November, the cumulative data point associated with November would be identified as "BCWP(CUM)." Similarly, the cumulative data points for August, September, and October, would be described by "BCWP(CUM-3)," "BCWP(CUM-2)," and "BCWP(CUM-1)," respectively.

Variances and Indices. A number of variances and indices are used by the EAC formulas to calculate estimates at completion. These equations are discussed below and later will be incorporated into the EAC formulas.

$$\text{COST VAR \%} = [(\text{BCWP(CUM)} - \text{ACWP(CUM)})/\text{BCWP(CUM)}] * 100 \quad (1)$$

This variance measures whether work accomplished to date is "over" or "under" budget. A negative cost variance percentage indicates actual work accomplished is costing this percentage more than planned (cost overrun). Similarly, a positive value indicates actual work accomplished is costing this percentage less than planned (cost underrun).

$$\text{CUR MON CPI} = (\text{BCWP(CUM)} - \text{BCWP(CUM-1)})/(\text{ACWP(CUM)} - \text{ACWP(CUM-1)}) \quad (2)$$

This is a Cost/Performance Index for the current month which indicates how much planned work the contractor performed for each dollar that was actually spent. For example, if the value for CUR MON CPI was .75, this means that for every dollar actually spent in the current month, only $.75 worth of work was performed.

THREE MON CPI = (BCWP(CUM) - BCWP(CUM-3))/

(ACWP(CUM) - ACWP(CUM-3)) (3)

Similar to CUR MON CPI except this index is a measure of the contractor's cost performance for the last three months.

CUM CPI = BCWP(CUM)/ACWP(CUM) (4)

This Cost/Performance Index is a measure of the contractor's cost performance from the start of the contract through the latest month for which data is available.

SCH VAR % = [(BCWP(CUM) - BCWS(CUM))/BCWS(CUM)]

* 100 (5)

This variance measures whether work accomplished to date is "behind" or "ahead" of schedule. A negative schedule variance percentage indicates this percentage less work was performed than scheduled (behind schedule). Similarly, a positive value indicates this percentage more work was performed than scheduled (ahead of schedule).

EAC Formulas. Four of the formulas used by AFWAL's Cost Performance Report Analysis (CPRA) computer program to generate estimates at completion have been reproduced from Capt Price's thesis and are shown below. Throughout the remainder of this thesis, these formulas will be referenced by the indicator, "EACn," where "n" is a number from 1 to 4 corresponding to a particular EAC technique.

EAC1 = ACWP(CUM) + (BCWR(CUM)/CUR MON CPI) (6)

where

BCWR(CUM) = BAC - BCWP(CUM) (7)

This formula takes into account all cost overruns that have occurred to date in the form of ACWP(CUM), but assumes such overruns are nonrecurring. It also assumes the remaining work will be performed with the same budget efficiency as the most recent month (CUR MON CPI).

$$EAC2 = ACWP(CUM) + (BCWR(CUM)/THREE\ MON\ CPI) \quad (8)$$

This method accounts for any cost overruns to date (ACWP(CUM)) and assumes the contractor will perform the remaining work with the budget efficiency displayed during the last three months (THREE MON CPI).

$$EAC3 = ACWP(CUM) + (BCWR(CUM)/CUM\ CPI) \quad (9)$$

This calculation also accounts for all cost overruns to date (ACWP(CUM)), but assumes the remaining work will be performed with the same budget efficiency exhibited since the start of the contract (CUM CPI).

$$EAC4 = ACWP(CUM) + ETC \quad (10)$$

where

$$ETC = [100 - (COST\ VAR\ \%) - .75 * (SCH\ VAR\ \%)] * BCWR(CUM)/100 \quad (11)$$

This technique includes the cost overruns to date (ACWP(CUM)), but also assumes the cost variance percentage will remain constant for the remainder of the program. Additionally, a penalty of 75% of the schedule variance percentage is used to compute catch-up. (It is believed that a typographical error exists in Price's thesis for this equation--in order to assess a "penalty" of 75% of the schedule variance percentage, the equation must be changed to read "-.75," rather than "+ .75"; therefore, the equation was altered.)

Scope and Limitations

This thesis conducted an evaluation of the robustness of four methods for calculating program estimates at

completion under a variety of simulated program scenarios. These four models represent only a small subset of the EAC techniques available to analysts and it should not be inferred that these are the "best" techniques for computing EACs. Additionally, each of these formulas compute EACs based on the contractor's past performance. As such, the ability of the formulas to accurately predict a program's final cost is limited if the program is new and little data is available. Also, this research simulated only a number populations representing a variety of possible cost overrun scenarios. These populations are, by no means, exhaustive of the possible scenarios that could exist in the "real" acquisition environment; but, it is believed there is sufficient variability in the scenarios to allow conclusions to be drawn about the robustness of the various EAC techniques examined.

Research Objective

The research hypothesis is that statistical evaluation of each of the four selected models for generating estimates at completion may suggest a robust technique. The research objective was to determine the robustness of each of these techniques under a number of simulated cost overrun scenarios.

Research Questions. Answers to the following research questions will be determined during this research.

1. What are the statistical moments associated with the EAC distributions generated by the four techniques under various simulated cost and schedule overrun situations?

2. Are there significant differences in the mean and variance of the EAC distributions generated by different EAC models for a given cost and schedule overrun scenario? by the same EAC model for various cost and schedule overrun scenarios?

3. Which EAC technique is the most robust for given cost and schedule overrun scenarios?

II. LITERATURE REVIEW

The literature review presents background information on topics relevant to this research project. Specifically, the topics discussed will be 1) Cost/Schedule Control Systems Criteria, 2) estimates at completion of contract costs, and 3) Monte Carlo simulation.

Cost/Schedule Control Systems Criteria

Department of Defense Instruction (DODI) 7000.2, Performance Measurement for Selected Acquisitions, first issued in 1967, requires incorporation of the Cost/Schedule Control Systems Criteria (C/SCSC) in all major systems acquisitions (excluding fixed price contracts) (1:45; 17:11). Major systems acquisitions are defined by DOD Directive 5000.1 and Office of Management and Budget Circular A-109 as programs with estimated research, development, and test (RDT&E) costs in excess of $200 million or estimated production costs in excess of $1 billion (12:1). However, these are not "hard" thresholds--the DOD acquisition command may authorize deviations from these thresholds if it is deemed appropriate. "There may be just cause for applying the criteria to other programs or specific contracts such as programs designated by the military departments as major system programs of national interest to DOD or the Congress because of their critical nature, risk involved or national

security" (8:44). Fixed price contracts are excluded because the contractor is assuming the cost and schedule risks; if the contractor's internal management system is inefficient, overruns will occur and profits will be lost. Conversely, in cost sharing type contracts, more efficient management by the contractor translates into reduced costs to the government (19:36-37).

Objectives. Abba states the objectives of the C/SCSC are:

- For contractors to use effective internal cost and schedule management control systems, and

- For the government to be able to rely on timely and auditable data produced by those systems for determining product-oriented contract status (1:45).

Both objectives could be accomplished by a variety of management control systems. An important aspect of the C/SCSC is that it is not a system--it does not impose a particular internal management system on the contractor. It is a set of criteria or standards that define an acceptable contractor management control system (1:45; 2:32; 18:36). The concept of the C/SCSC is that if a contractor already operates an adequate cost and schedule management control system, the program office should be able to extract the required information regarding project status (9:15). Incorporating the C/SCSC is not intended to replace or duplicate a contractor's existing system--changes "are required only to the extent that it does not meet the criteria" (1:45).

Requirements. Department of Defense Instruction 7000.2 and the C/SCSC joint implementation guide specify the requirements a contractor's internal management system must possess to be acceptable to the DOD--the "what" and not the "how." "Briefly stated, C/SCSC requires the contractor to define the work required to meet contract objectives, assign the work to specifically identified organizational elements, establish internal schedules and budgets, and periodically compare actual cost and schedule performance against the planned budgets and schedules" (19:37). The guide outlines in five broad categories 35 criteria that must be met by the contractor's system. The five categories include organization, planning and budgeting, accounting, analysis, and revision and access to data (2:33; 8:16-17).

Organizational Criteria. These criteria require the contractor to precisely define all contractual work. This is accomplished by using a work breakdown structure (WBS) which breaks up the total effort into specific units of work or work packages. Additionally, the contractor must clearly identify the appropriate functional organizational level or manager for each of the work units. This level becomes a management control point where the contractor will establish cost accounts to allow cost control and monitor performance (9:16; 15:29-30).

Planning and Budgeting Criteria. These criteria require the contractor to systematically schedule, budget, and authorize the total contractual effort. The contractor must devise a master schedule that identifies key milestones and work interdependencies, a budgeting system that allocates the total budget to each of the WBS elements and functional organizations, and a work authorization system that assigns defined tasks to the appropriate functional organizations. A critical element of these criteria is the development of a time-phased budget known as the performance measurement baseline (9:16; 15:30). The authorized work is scheduled "in time-phased 'planned value' increments...as work is accomplished, it is 'earned' on the same budget dollar basis" (1:45). Comparing the earned and planned values provides a measure of contract performance in the form of a schedule variance.

Accounting Criteria. These criteria require the contractor to accumulate the actual costs, direct and indirect, of all the accomplished work. Direct costs must be identified at the cost account level for summarization to higher management, but indirect costs may be allocated at some higher level. However the indirect costs are allocated, cost data must be summarized by both the work breakdown structure and functional organization. A comparison of actual cost with earned value yields a cost

variance which indicates whether or not the contractor is under- or overrunning the budget (1:45; 8:16; 15:30).

Analysis Criteria. These criteria describe the "characteristics that contractors' systems must possess, and specify the type of data that should be derived from the contractors' systems to adequately measure and address performance" (9:16). A number of key terms are introduced by the analysis criteria, some of which include:

1. Actual Cost of Work Performed (ACWP). The costs actually incurred by the contractor in performing the work during a given time period (6:5).

2. Budget at Completion (BAC). The budgeted amount for the total work to be accomplished under the contract (5:5).

3. Budgeted Cost for Work Performed (BCWP). The amount budgeted for the work actually performed (6:6).

4. Budgeted Cost for Work Scheduled (BCWS). The amount budgeted for the work scheduled to be completed during a given time period (6:6).

5. Estimate at Completion (EAC). The actual costs of the work performed to date plus an estimate of the costs to complete the remaining authorized work (6:6).

(These terms were defined in the first chapter.) The schedule variance can be determined by comparing BCWS and BCWP and indicates whether work is behind or ahead of schedule. Although the schedule variance will be stated in terms of dollars rather than in units of time, it is an early "flag" of potential problems and indicates the need for more detailed analysis. Similarly, the cost variance can be determined by comparing BCWP and ACWP (2:34; 15:31).

The system employed by the contractor must provide a summary of these elements and the associated variances, and an analysis of variances if predetermined thresholds are exceeded (9:17).

Revisions and Access to Data. These criteria "require the contractor to do basically two things: (1) maintain a valid performance measurement baseline, and (2) provide government access to internal data" (9:17).

Reporting. Interestingly, the C/SCSC has no requirements for external reporting. "Summary data from the [contractor's] internal system are reported to the government through the Cost Performance Report (CPR), as specified on the Contract Data Requirements List" (1:46). Typically, the CPR is submitted monthly to the government program office and reports summary information collected by the contractor's C/SCSC-compliant internal management system. Normally, detailed information is not necessary (unless a problem exists) because C/SCSC has "guaranteed" that objective cost and schedule information has been provided by the contractor. This permits program management to focus their attention on problem areas and take timely corrective action. In addition to confirming problems, information contained in the CPR is used to project variance trends to contract completion and to forecast completion dates and final contract costs (1:46).

Estimates at Completion of Contract Costs

As mentioned previously, summary data from a contractor's internal management control system are reported to the government through the CPR. One of the key data items required by this report is the contractor's Latest Revised Estimate of the contract's cost at completion, or EAC. These estimates are useful tools for the program office to verify funding requirements identified by a contractor on the Contract Funds Status Report (1:46-47). Additionally, "EAC's are a primary input into the Selected Acquisition Reports (SAR's) which go to major acquisition commands and eventually end up in Congress" (5:ii).

The contractor's EAC should consist of the actual cost of work performed to date plus the latest estimate of the cost to complete the remaining work. The joint implementation guide provides an explicit checklist for reviewing the procedures and data used by contractors to generate EAC's. Numerous methods exist for generating EAC's and the criteria do not specify a particular method that the contractor must use. A number of methods for generating EACs are discussed by Bowman including: indices, weighting systems, expectations theory, and a variety of hybrid techniques (4). However, whatever methodology is selected by the contractor, it must be rational, consistent, and reconcilable (6:47).

The important words in the last sentence are "rational," "consistent," and "reconcilable." There appears to be no one "best" way to compute EACs--each technique will normally yield a different estimate at completion. The problem is that numbers can be manipulated mathematically to produce the desired results, accurate or not. Therefore, it is important that, whatever method is selected, it must be rational; any technique that produces an EAC which approaches the true value should be favored (5:2,23). As well as being rational, the method must be applied consistently. "If the methods change (regardless of the reason) then a rubber baseline is generated...and the resultant EAC loses its meaning" (5:23). Finally, the contractor's estimates of costs at completion must be reconcilable with cost data reported to the government program office (6:47).

In the search for the "best" method of generating an EAC, Holeman points out "Emphasis needs to be placed in this area to first determine whether a reasonable quantitative approach is available and then decide the limitations to this approach" (11:41). However, there seems to be very little research in this area to date. Price examined six automated techniques for computing EACs (four of which are the basis of this research) used by AFWAL's Cost Performance Report Analysis program. The results of his research indicate the EAC method using a

weighted Cost/Performance Index and Schedule/Performance Index was the "best predictor" (explained the highest percentage of variation), while the method based on the monthly Cost/Performance Index was the poorest predictor (15:31-32). (These techniques correspond to EAC4 and EAC1, respectively, of this report.) Aside from Price's research (which was limited to cost data for on-going research and development programs), the literature review revealed little additional information regarding the accuracy or applicability of various EAC methods.

Monte Carlo Simulation

"Monte Carlo methods comprise that branch of experimental mathematics which is concerned with experiments on random numbers" (10:2). The use of Monte Carlo analysis as a research tool has its origins in the 1940's when John von Neumann and S. Ulam simulated the probabilistic problems associated with the shielding of nuclear devices; the problems were too risky and expensive to solve experimentally, and too complicated to solve analytically (10:8; 16:135).

There are two types of problems handled by Monte Carlo methods--probabilistic and deterministic. In either case, the objective of most Monte Carlo analysis is to estimate the unknown value of some parameter associated with some population distribution (10:2,16). Hammersley describes the case of a probabilistic problem (which is of primary

concern to this research):

> the simplest Monte Carlo approach is to observe random numbers, chosen in such a way that they directly simulate the physical random processes of the original problem, and to infer the desired solution from the behaviour of these random numbers (10:2).

Thus, the common idea behind the collection of techniques referred to as "Monte Carlo analysis" is "approximating the solution to a problem by sampling from a random process" (17:135-136). Stated differently by Hammersley:

> the essential feature common to all Monte Carlo computations is that at some point we have to substitute for a random variable a corresponding set of actual values having the statistical properties of the random variable (10:25).

Summary

This chapter presented background information on three areas relevant to this research project. First, the Cost/Schedule Control Systems Criteria, or C/SCSC, was examined. The C/SCSC describe the various criteria, or standards, that a contractor's internal management control system must meet to be acceptable to the government. An important aspect of the C/SCSC is that it is not a system--it does not impose a particular management control system on the contractor.

Second, literature pertaining to estimates at completion of contract costs was presented. Estimates at completion, EACs, should include the contractor's actual cost of work completed to date plus an estimate of the cost to complete the remaining contractual work. There appears

to be very little research in the area of identifying a "best" method for calculating EACs.

Finally, Monte Carlo simulation was addressed. The types of problems handled by Monte Carlo methods include probabilistic and deterministic. In both cases, the usual objective is to approximate the unknown value of a population parameter by sampling from a random process.

III. METHODOLOGY

Introduction

To analyze the robustness and compute the statistical moments associated with each of the estimate at completion techniques, it would have been ideal to have had actual data from completed programs. However, there was insufficient time to collect actual data and manipulate it into a usable format. Therefore, Monte Carlo simulation methods were used to generate sufficient data to answer the research questions.

This research investigated samples from 18 simulated populations corresponding to the possible combinations of the following: a low and high range for the monthly BCWP values, means of -10, -20, and -30 (percent) for the cost variance percentage distributions (cost overrun scenarios), and means of 0, -5, and -10 for the schedule variance percentage distributions (on schedule and two behind schedule scenarios). The computer program used for most of this research was S. S is a UNIX-based software system that provides the user with "an interactive environment for data analysis and graphics" (3:i). S was considered to be particularly suitable for this application because of its ease of use and its ability to generate random samples from a variety of distributions.

Assumptions

Since Monte Carlo simulation methods were used to generate the required data values for this research, it was necessary to make certain simplifying assumptions concerning how much data was to be generated and how it was to be accomplished. The first assumption was that all simulated "programs," or contracts, span 60 months. Hence, data values were generated as if each program lasted five years--it began in month one and ended in month sixty.

The second assumption was that the monthly BCWP values lie in one of two ranges, or strata--a "low" range consisting of monthly values from $0 to $500,000 and a "high" range consisting of values from $500,000 to $15,000,000. This stratification makes it possible to evaluate the capabilities of each of the EAC techniques for low- and high-value contracts.

The third assumption concerns the distributions of the cost and schedule variance percentages. It was assumed that both were normally distributed with a standard deviation of 2.5 percent. Examination of the database used by Price appears to support this assumption--while smaller valued, shorter duration contracts exhibited larger standard deviations in these parameters; the standard deviations were significantly reduced for larger valued contracts for which more data was available.

The fourth assumption was that the starting month for calculations (the simulated last month for which data was available) was uniformly distributed between months 4 and 59. This assumption was made because Eq (7) (EAC2) uses the three month Cost/Performance Index, THREE MON CPI, which requires at least 3 months of data. Also, it makes little sense to calculate an EAC if the program has been completed (month 60).

Finally, it was necessary to simulate values for the actual and budgeted costs at completion. Therefore, it was assumed that the last available ACWP value, ACWP(60), represented the actual contract cost at completion. Similarly, the last available BCWP value, BCWP(60), was assumed to simulate the contract's budgeted cost at completion, or BAC. This method is similar to that used by Price (15).

Robustness Measure

As discussed in Chapter I, the definition of a "robust" estimate is subjective; it depends upon who is using the estimate and their criteria for what they consider an acceptable result (13:1). This research is interested in comparing the robustness of various techniques for estimating a contract's cost at completion; therefore, a measure of robustness is needed before any comparisons can be made. For the purposes of this research, the following operational definition of a

robustness measure, RM, will be used:

$$RMn = (EACn - ACWP(60))/ACWP(60) \quad (12)$$

where

n corresponds to one of the four EAC techniques

and

ACWP(60) represents the contract completion cost

Therefore, a value of -.15 for RM1 indicates that the EAC1 technique resulted in an estimate at completion that was 15 percent below the simulated actual contract completion cost. Similarly, a value of .10 for the robustness measure indicates an estimate that was 10 percent above the actual value.

Methodology and S Program

After making the above assumptions and defining the robustness measure, it was necessary to develop an S program that would simulate actual data found in a Cost Performance Report and perform the EAC and robustness calculations for each of the 18 populations. The program developed for this purpose can be found in Appendix A and each of the steps in the process is discussed below.

Since each simulated program was assumed to last 60 months, the first step was to generate 60 monthly BCWP values for the selected range (low or high) from a uniform distribution. This was accomplished by using the random number generator located in S which permits random sampling

from a uniform distribution with specified lower and upper bounds. These values were then summed to obtain the cumulative BCWP values needed in later calculations.

The second step was to generate 60 monthly values from normal distributions for both the cost variance percentage and schedule variance percentage. Again, a random number generator contained in S was used to randomly sample 60 values for each variable from separate normal distributions with standard deviations of 2.5 percent and means corresponding to the selected cost and schedule overrun scenarios.

To compute the various indices and EACs, it was necessary to have the cumulative monthly values for ACWP and BCWS. Therefore, the third step was to calculate values for these variables using the cumulative BCWP values, the monthly cost variance percentages, and the monthly schedule variance percentages, generated in the preceding steps. This was done by rearranging Eqs (1) and (5) to obtain the following:

$$ACWP(m) = BCWP(m) * (1. - COST\ VAR\ \%(m)/100.) \qquad (13)$$

and

$$BCWS(m) = BCWP(m)/(1. + SCH\ VAR\ \%(m)/100.) \qquad (14)$$

where

m = a particular month from 1 to 60

For example, the cumulative monthly value of BCWP for month

25, BCWP(25), was used in addition to the randomly generated values for the cost and schedule variance percentages for that month to compute ACWP and BCWS for month 25, ACWP(25) and BCWS(25) respectively.

With the 60 cumulative monthly values for BCWP, ACWP, and BCWS, the fifth step was to determine the starting month for calculations--the simulated last month for which data was available. This was done so that EACs would be computed for programs simulated in various stages of completion. A sequence of integers from 4 to 59 was generated and a single value was randomly chosen to represent the last month for which data was available; this month was designated by the indicator, "(CUM)," in Eqs (1)-(12).

The sixth step was to use the data generated by the previous steps to calculate the various indices given by Eqs (2)-(4). Then, these indices were used in addition to other data values to compute estimates of the contract's cost at completion for each of the four EAC models, Eqs (6)-(10).

After calculating the EACs and having the simulated actual contract cost at completion, ACWP(60), it was possible to compute the robustness measures associated with each of the EAC techniques. Thus, the final step was to use Eq (12) to determine the robustness measure for each of the four estimate at completion techniques.

The seven steps described above were replicated 300 times and the pertinent data stored in a matrix. Hence, estimates at completion and robustness measures for each of the EAC models were computed for 300 programs, or contracts, in various stages of completion. A sample size of 300 should be sufficiently large so that summary statistics associated with the samples can be assumed to have been derived from approximately normal distributions (7:199; 13:5-6).

In order to address the research questions, it was necessary to compute the statistical moments of the distributions associated with each of the four EAC techniques. Therefore, the mean, standard deviation, and variance, were calculated for each of the EAC and robustness measure distributions. In the case of the variance (and hence, the standard deviation), S assumes it is working with a population rather than a sample. As a result, when computing the sample variances, it was necessary to multiply the variances computed in S by the expression, "n/(n-1)," where "n" is the sample size--in this particular case, n=300.

The procedures discussed in this section were performed for samples from each of the 18 populations.

IV. Results and Discussion

Introduction

This chapter presents the results of the analysis performed on the data generated by the procedures described in the previous chapter. The results are discussed in the order of the research questions outlined in Chapter I. First, the statistical moments associated with the distributions generated by each of the four EAC techniques under various simulated cost and schedule overrun scenarios is presented. Next, differences in the statistical moments are discussed--both the differences between the four techniques for a given population, and for a particular technique between various populations. Finally, the robustness of the four EAC models is discussed.

Due to the large number of populations simulated in this research, the following nomenclature is used to identify the individual populations. Each population is distinguished with a four or five character label. The first two digits identify the cost overrun scenario, the third character represents the BCWP range, and the fourth (and fifth, if required) digit identifies the schedule overrun scenario. For example, "20L10" represents the simulated population with a cost variance percentage of -20 percent, BCWP values from the "low" range, and a schedule variance percentage of -10 percent. Similarly, "10H0"

represents the simulated population with a cost variance percentage of -10 percent, BCWP values from the "high" range, and a schedule variance percentage of 0 percent (on schedule).

Results of Research Question 1

The first research question was to determine the statistical moments of the EAC distributions that resulted from generating estimates at completion with each of the four techniques for each of the simulated populations. The statistical moments associated with the four EAC techniques, EAC1-EAC4, can be found in Tables 1-4, respectively, of Appendix B. Additionally, the summary statistics for each of the individual populations are located in Tables 9-26 of Appendix D.

Results of Research Question 2

The second research question asked if there are significant differences in the means and variances of the distributions generated by different EAC models for a given cost and schedule overrun scenario and, also, by the same model for various scenarios. Examination of Tables 1-4 of Appendix B reveals that the means of the distributions associated with EAC2, EAC3, and EAC4, are comparable--not only for a particular population, but across the various populations as well. However, for a particular population and over all the populations, the means associated with the

EAC1 distributions were consistently larger than those of the other three techniques. This indicates that, in general, use of the EAC1 model results in larger estimates at completion in a cost overrun situation than the other techniques researched. Each of the techniques responded to the increased cost overruns by increased estimates at completion. In other words, as the cost variance percentage "increased" from -10 percent to -30 percent, each of the techniques "recognized" a larger cost overrun and increased its estimate at completion. However, the different values for the schedule variance percentage had no noticeable impact on the estimates of the EAC4 model--the only EAC technique examined that incorporates the schedule variance percentage. This may be attributable to the smaller values selected for the schedule variance percentage.

In the case of the variances, Tables 1-4 indicate that the variances of the EAC distributions associated with EAC3 are consistently lower than those of the other techniques, though the variances of the EAC4 distributions are very similar. This is true for any particular population and overall. The variances for the EAC2 distributions are slightly larger than those of EAC3 and EAC4, but are still much smaller than those of EAC1; the variances of the EAC1 distributions are consistently much larger than for the other models. This behavior most likely results from the

fact that EAC1 is based on the current month's cost performance index which may change dramatically from one month to the next; the other techniques all use some form of "smoothing" to lessen the impact of month-to-month changes. As might be expected, when the cost overruns increased, the variances associated with each of the EAC models increased also. Again, the variances of the EAC4 distributions seemed unaffected by the increased schedule variance percentages.

Results of Research Question 3

The third research question was concerned with identifying the EAC technique which is most robust for a particular cost and schedule overrun scenario. The summary statistics for the robustness measures can be found in Tables 5-8 of Appendix C. One characteristic of all the EAC models is immediately apparent from these tables--for every simulated population, all of the models underestimated the simulated completion cost. This is indicated by negative values for all of the means associated with the robustness measure distributions. That is not to say there were no instances in which the models overestimated the completion cost, but, in general, the tendency for each of the EAC techniques was to underestimate the final cost.

Further examination of Tables 5-8 yields the following results concerning the means and variances of the

robustness measure distributions. The means for the distributions ranged in value from approximately -.14 to -.43 which indicates estimates at completion of contract costs from 14 to 43 percent below the "actual" cost. The means of the robustness measure distributions associated with EAC1 were consistently the lowest; this was expected since the means of the EAC distributions for EAC1 were the largest. The means of the robustness measure distributions resulting from EAC3 and EAC4 were comparable though slightly larger than those of EAC2. This behavior is evident for any of the particular populations, as well as across all the populations.

There are several interesting observations regarding the behavior of the robustness measure means as the cost variance percentage increased (increased overruns). When the cost overruns increased, the means of the robustness measure distributions for each of the EAC techniques decreased (smaller absolute value). As mentioned above, the means for EAC2, EAC3, and EAC4, are similar and, interestingly, they all followed the same pattern of reduction (approximately -.42 to -.31) when the cost variance percentage increased for both the low and high range of the BCWP values. This suggests that each of these techniques, EAC2-EAC4, is more sensitive to the magnitude of the cost variance percentage than the BCWP value. However, the same is not true for EAC1. As the cost

variance percentage increased, the robustness measure means of EAC1 decreased much less for the high BCWP range than for the low suggesting that EAC1 is affected not only by changes in the cost variance percentage, but changes in the magnitude of the BCWP values as well.

The variances displayed similar behavior patterns. In all cases, as the cost overruns increased, the variances of the robustness measure distributions associated with each of the EAC techniques increased. The variances for EAC3 and EAC4 were comparable and, generally, the lowest for all of the populations; though the variances for EAC2 were only slightly higher. Again, as the cost variance percentage increased, the variances for EAC2-EAC4 followed a similar pattern of increase for both ranges of the BCWP values. Additionally, this pattern was over a relatively narrow band (.09 to .13) for EAC3 and EAC4. The variances associated with EAC1 were consistently the largest and increased dramatically as the cost variance percentage increased for the low range of BCWP values.

Summary

For the given set of cost and schedule overrun scenarios selected for this research project, the tendency of all four of the EAC models was to underestimate the contract's final cost. The values for the means of the robustness measure distributions ranged from approximately -.14 to -.43 indicating underestimates ranging from 14 to

43 percent of the contract's cost at completion. For a particular population, the means associated with EAC1 were lowest of the four techniques in all cases, but the corresponding variances were also significantly larger. Of the four models, EAC1 was the only technique seemingly sensitive to the magnitude of the BCWP values in addition to changes in the cost variance percentages. The variances of the robustness measures associated with EAC2, EAC3, and EAC4, were comparable to one another and relatively stable across all of the simulated populations.

V. Conclusions

Review of the Hypothesis

The research hypothesis was that a statistical evaluation of each of the EAC models for generating estimates at completion of contract costs may identify a robust technique. This hypothesis was tested using Monte Carlo simulation techniques to calculate estimates at completion for a number of simulated cost and schedule overrun scenarios.

Conclusions

The results presented in the preceding chapter suggest that none of the selected EAC techniques are robust for the cost and schedule overrun scenarios that were examined. Though a measure's "robustness" is subjective, for practical purposes, it would be desirable to have an estimate at completion technique that could reliably estimate a contract's final cost within five or ten percent over a wide range of situations. All of the EAC techniques in this research failed to approach this desired threshold. The statistical means of the robustness measure distributions for EAC2, EAC3, and EAC4, indicate they were unable to consistently predict a contract's completion cost within 30 percent. However, the variances of the robustness measures associated with these techniques were relatively stable across all of the simulated populations

suggesting the possibility that they could be modified to more accurately predict the final contract cost; thus, making them more robust. The means of the robustness measure distributions for EAC1 were lower than those of the other three models for individual populations; however, the large variances associated with EAC1 and it's apparent sensitivity to the magnitude of the BCWP values make it a very unreliable predictor of a contract's completion cost.

Additionally, for all of the simulated cost and schedule overrun scenarios, the tendency of each of the EAC techniques was to underestimate the contract's final cost. This tendency may have serious implications for the program office in this time of increased media attention, Congressional oversight, and growing budget deficits.

Recommendations for Future Research

These conclusions were based on Monte Carlo simulation methods and, as with any simulation, it may be appropriate to question their applicability to the "real world." Therefore, future research could analyze these EAC techniques with actual data from completed programs to verify the reasonableness of these conclusions and, hence, the methods that were used in this research. Also, it may be beneficial to apply this methodology to other EAC techniques, or modifications to the models used in this research, to determine if more robust models exist. Lastly, future research could analyze these and other

techniques in terms of acquisition phase (full scale development, production, etc.), contract type, percentage of contract completed, or type of contract deliverable. Research in these areas could identify robust methods for calculating estimates at completion of contract costs, or determine which EAC techniques are best suited for a particular set of conditions.

Appendix A: S Program

```
#**********************************************************
#
#     Author:  Capt Darren E. Morgan
#
#     Written:  May 1987
#
#**********************************************************
#
options(echo=2)
#
#
#    POPULATION FOR THIS RUN:  20H10
#
#
#    SET LOWER AND UPPER LIMITS FOR
#      MONTHLY BCWP VALUES
#
#    LOWER LIMIT
lowlim_500000.
#
#    UPPER LIMIT
uplim_15000000.
#
#
#    SET VALUES FOR MEAN AND STD. DEV.
#      OF COST VARIANCE PERCENTAGES
#      (NEG. VALUE => COST OVERRUN)
#
#    MEAN
cvmu_-20.
#
#    STD. DEV.
cvsigma_2.5
#
#
#    SET VALUES FOR MEAN AND STD. DEV.
#      OF SCHEDULE VARIANCE PERCENTAGES
#      (NEG. VALUE => BEHIND SCHEDULE)
#
#    MEAN
svmu_-10.
#
#    STD. DEV.
cvsigma_2.5
#
#
#    SET-UP MATRIX TO HOLD DATA VALUES
#
```

```
n_300
case1_matrix(0,n,15,byrow=TRUE)
#
#
#   CREATE LOOP TO COMPUTE n=300 VALUES
#
for(rowv in 1:n) [
#
#
#   RANDOMLY SELECT 60 MONTHLY VALUES FOR BCWP
#     FROM A UNIFORM DISTRIBUTION WITH THE
#     LOWER AND UPPER BOUNDS SET ABOVE
#
bcwpinit_runif(60,lowlim,uplim)
#
#
#   CALCULATE CUMULATIVE VALUES FOR BCWP
#
bcwp_cumsum(bcwpinit)
#
#
#   RANDOMLY SELECT 60 MONTHLY VALUES FOR
#     COST VARIANCE PERCENTAGE AND SCHEDULE
#     VARIANCE PERCENTAGE FROM NORMAL
#     DISTRIBUTIONS WITH THE MEANS AND STANDARD
#     DEVIATIONS SET ABOVE
#
cvpctg_rnorm(60,cvmu,cvsigma)
svpctg_rnorm(60,svmu svsigma)
#
#
#   CALCULATE THE CUMULATIVE MONTHLY VALUES
#     FOR ACWP
#
acwp_bcwp*(1.-cvpctg/100.)
#
#
#   CALCULATE THE CUMULATIVE MONTHLY VALUES
#     FOR BCWS
#
bcws_bcwp/(1.+svpctg/100.)
#
#
#   SET UP A SEQUENCE OF VALUES FROM 4-59
#     REPRESENTING POSSIBLE STARTING MONTHS
#     FOR ESTIMATE AT COMPLETION CALCULATIONS
#
mths_seq(4,59,1)
#
#
#   RANDOMLY SELECT A STARTING MONTH FROM THE
#     ABOVE SEQUENCE TO SERVE AS THE STARTING
```

```
#     MONTH FOR ESTIMATE AT COMPLETION CALCULATIONS
#
stpt_sample(mths,1)
#
#
#   CALCULATE THE CURRENT MONTH, THREE MONTH
#     AND CUMULATIVE COST PERFORMANCE INDICES
#
cmcpi_(bcwp[stpt]-bcwp[stpt-1])/(acwp[stpt]-
      acwp[stpt-1])
thmcpi_(bcwp[stpt]-bcwp[stpt-3])/(acwp[stpt]-
       acwp[stpt-3])
cumcpi_bcwp[stpt]/acwp[stpt]
#
#
#   COMPUTE ESTIMATES AT COMPLETION USING
#     THE FOUR EAC TECHNIQUES
#
eac1_acwp[stpt]+(acwp[stpt]-bcwp[stpt])/cmcpi
eac2_acwp[stpt]+(acwp[stpt]-bcwp[stpt])/thmcpi
eac3_acwp[stpt]+(acwp[stpt]-bcwp[stpt])/cumcpi
  etc_(100.-cvpctg[stpt]-.75*svpctg[stpt])*
      (scwp[stpt]-bcwp[stpt])/100.
eac4_acwp[stpt]+etc
#
#
#   COMPUTE ROBUSTNESS MEASURES FOR EACH
#     OF THE EAC TECHNIQUES
#
rm1_(eac1-acwp[60])/acwp[60]
rm2_(eac2-acwp[60])/acwp[60]
rm3_(eac3-acwp[60])/acwp[60]
rm4_(eac4-acwp[60])/acwp[60]
#
#
#   SAVE DATA IN MATRIX
#
case1[rowv,1]_uplim
case1[rowv,2]_cvmu
case1[rowv,3]_cvsigma
case1[rowv,4]_svmu
case1[rowv,5]_svsigma
case1[rowv,6]_eac1
case1[rowv,7]_eac2
case1[rowv,8]_eac3
case1[rowv,9]_eac4
case1[rowv,10]_rm1
case1[rowv,11]_rm2
case1[rowv,12]_rm3
case1[rowv,13]_rm4
case1[rowv,14]_stpt
case1[rowv,15]_acwp[60]
```

```
#
#
#   CLOSE "FOR" LOOP
  ]
#
#
#   COMPUTE SAMPLE MEAN, VARIANCE, AND STD. DEV.
#     FOR OUTPUT ASSOCIATED WITH EACH EAC TECHNIQUEE
#
#   EAC1
mean(case1[,6])
var1_var(case1[,6])*n/(n-1)
var1
sqrt(var1)
#
#   EAC2
mean(case1[,7])
var2_var(case1[,7])*n/(n-1)
var2
sqrt(var2)
#
#   EAC3
mean(case1[,8])
var3_var(case1[,8])*n/(n-1)
var3
sqrt(var3)
#
#   EAC4
mean(case1[,9])
var4_var(case1[,9])*n/(n-1)
var4
sqrt(var4)
#
#
#   COMPUTE THE MEAN, VARIANCE, AND STD. DEV.
#     FOR EACH OF THE ROBUSTNESS MEASURES
#
#   RM1
mean(case1[,10])
varrm1_var(case1[,10])*n/(n-1)
varrm1
sqrt(varrm1)
#
#   RM2
mean(case1[,11])
varrm2_var(case1[,11])*n/(n-1)
varrm2
sqrt(varrm2)
#
#   RM3
mean(case1[,12])
varrm3_var(case1[,12])*n/(n-1)
```

```
varrm3
sqrt(varrm3)
#
#   RM4
mean(case1[,13])
varrm4_var(case1[,13])*n/(n-1)
varrm4
sqrt(varrm4)
#
#
#   COMPUTE MEAN, VARIANCE, AND STD. DEV.
#     FOR THE STARTING POINT
#
mean(case1[,14])
varstpt_var(case1[,14])*n/(n-1)
varstpt
sqrt(varstpt)
#
#
#   COMPUTE THE MEAN, VARIANCE, AND STD. DEV.
#     FOR THE FINAL ACWP VALUE (SIMULATED
#     FINAL CONTRACT COST)
#
mean(case1[,15])
varacwp_var(case1[,15])*n/(n-1)
varacwp
sqrt(varacwp)
#
#
#   OUTPUT DATA MATRIX
#
case1
```

Appendix B: Statistical Moments of EAC Distributions

Table 1

Statistical Moments of EAC1 Distributions

Population	Mean	Variance	Std. Dev.
10L0	10552207.	1.004301e+14	10021483.
10L5	10222382.	1.917890e+14	13848790.
10L10	10021643.	1.571839e+14	12537300.
20L0	13815946.	1.379802e+15	37145684.
20L5	12113014.	6.668586e+14	25823604.
20L10	12857628.	2.633370e+14	16227658.
30L0	16645910.	2.687206e+15	51838260.
30L5	16524732.	2.759790e+15	52533704.
30L10	16629110.	2.687208e+15	51838284.
10H0	311815616.	4.206544e+16	205098592.
10H5	312075456.	5.103280e+16	225904432.
10H10	314948480.	4.706270e+16	216939440.
20H0	372786496.	8.399460e+16	289818240.
20H5	379096000.	1.036054e+17	321878000.
20H10	364959488.	1.444690e+17	380090656.
30H0	426566656.	2.365435e+17	486357000.
30H5	416611520.	1.871683e+17	432629504.
30H10	428850560.	2.361100e+17	485911520.

Table 2

Statistical Moments of EAC2 Distributions

Population	Mean	Variance	Std. Dev.
10L0	9693292.	2.789606e+13	5281672.
10L5	9484483.	2.765948e+13	5259228.
10L10	9529091.	2.635388e+13	5133603.
20L0	11628031.	3.435702e+13	5861486.
20L5	11279937.	4.1288770+13	6425550.
20L10	11533638.	4.092710e+13	6397431.
30L0	13674372.	4.855310e+13	6968005.
30L5	13362036.	5.388900e+13	7340911.
30L10	13646116.	4.830540e+13	6950208.
10H0	300046656.	2.650512e+16	162804000.
10H5	299169000.	2.443547e+16	156318464.
10H10	302756800.	2.282570e+16	151081776.
20H0	356882000.	3.863110e+16	196548000.
20H5	361350304.	3.319137e+16	182185000.
20H10	351440000.	3.880280e+16	196984272.
30H0	414407712.	5.381430e+16	231979000.
30H5	394192512.	4.644060e+16	215500800.
30H10	416608000.	5.269840e+16	229561312.

Table 3

Statistical Moments of EAC3 Distributions

Population	Mean	Variance	Std. Dev.
10L0	9589969.	2.591912e+13	5091082.
10L5	9351947.	2.516910e+13	5016882.
10L10	9404131.	2.410610e+13	4909795.
20L0	11520133.	3.175133e+13	5634831.
20L5	11087327.	3.572390e+13	5976948.
20L10	11413822.	3.663916e+13	6053029.
30L0	13546857.	4.391314e+13	6626699.
30L5	13200820.	4.809944e+13	6935376.
30L10	13516016.	4.365570e+13	6607248.
10H0	297163000.	2.483380e+16	157587408.
10H5	296437280.	2.314036e+16	152119536.
10H10	300169440.	2.168520e+16	147259000.
20H0	353678000.	3.510360e+16	187359488.
20H5	357890000.	3.065988e+16	175099600.
20H10	345994000.	3.393490e+16	184214272.
30H0	407460736.	4.561820e+16	213584192.
30H5	389761000.	4.108870e+16	202703472.
30H10	410118400.	4.486460e+16	211812592.

Table 4

Statistical Moments of EAC4 Distributions

Population	Mean	Variance	Std. Dev.
10L0	9591994.	2.594234e+13	5093362.
10L5	9382043.	2.534054e+13	5033939.
10L10	9464296.	2.443815e+13	4943496.
20L0	11519077.	3.175832e+13	5635452.
20L5	11146384.	3.610728e+13	6008933.
20L10	11535967.	3.747280e+13	6121504.
30L0	13545404.	4.392570e+13	6627646.
30L5	13290375.	4.878794e+13	6984836.
30L10	13694937.	4.485260e+13	6697207.
10H0	297225792.	2.485590e+16	157657568.
10H5	297388384.	2.329998e+16	152643296.
10H10	302044000.	2.197182e+16	148229000.
20H0	353794000.	3.515320e+16	187491840.
20H5	359740544.	3.099398e+16	176051000.
20H10	349659000.	3.467092e+16	186201280.
30H0	407476000.	4.561857e+16	213585000.
30H5	392229000.	4.167227e+16	204139000.
30H10	415633000.	4.609816e+16	214704800.

Appendix C: Statistical Moments of RM Distributions

Table 5

Statistical Moments of RM1 Distributions

Population	Mean	Variance	Std. Dev.
10L0	-.3596454	.377067	.614058
10L5	-.378712	.6658007	.815966
10L10	-.393657	.542814	.736759
20L0	-.2258958	5.26306	2.294136
20L5	-.3279834	1.97177	1.404197
20L10	-.284222	.834229	.913361
30L0	-.1369596	8.68556	2.947127
30L5	-.1432385	8.85594	2.975894
30L10	-.1376086	8.68554	2.947124
10H0	-.3901554	.1616249	.402026
10H5	-.395343	.206625	.45456
10H10	-.3894853	.1913368	.4374206
20H0	-.3314503	.271928	.521467
20H5	-.3258837	.359676	.59973
20H10	-.343044	.4570483	.6760535
30H0	-.29367	.64024	.80015
30H5	-.297774	.565738	.7521555
30H10	-.29059	.638918	.799324

Table 6

Statistical Moments of RM2 Distributions

Population	Mean	Variance	Std. Dev.
10L0	-.4123724	.1024277	.320043
10L5	-.419743	.1021418	.3195962
10L10	-.419882	.096849	.3112057
20L0	-.36086	.1002212	.3165773
20L5	-.367753	.127554	.357147
20L10	-.3589566	.1269422	.3562894
30L0	-.3063355	.1207366	.3474717
30L5	-.3220447	.1353002	.367832
30L10	-.3075712	.1201053	.346562
10H0	-.413259	.1012668	.3182245
10H5	-.4216004	.0895257	.2992085
10H10	-.4143805	.0826822	.287545
20H0	-.360192	.1244955	.352839
20H5	-.359221	.1012998	.3182763
20H10	-.365342	.1245045	.352852
30H0	-.3109253	.146631	.3829244
30H5	-.336999	.1256891	.3545266
30H10	-.3078258	.1438957	.379336

Table 7

Statistical Moments of RM3 Distributions

Population	Mean	Variance	Std. Dev.
10L0	-.418999	.094054	.3066823
10L5	-.427719	.0930635	.305063
10L10	-.4274625	.0884988	.297489
20L0	-.366683	.0925131	.3041596
20L5	-.378269	.1106666	.3326658
20L10	-.3662427	.111564	.334012
30L0	-.3126217	.1091058	.3303117
30L5	-.3301655	.1202938	.346834
30L10	-.3139995	.1084363	.3292967
10H0	-.4191976	.0940038	.3066003
10H5	-.4268747	.0845853	.2908354
10H10	-.4193546	.0784237	.2800423
20H0	-.3664585	.1115042	.3339224
20H5	-.365283	.0934018	.305617
20H10	-.3749374	.1091143	.3303246
30H0	-.3222148	.1245656	.3529386
30H5	-.344216	.1113792	.333735
30H10	-.3183693	.1227657	.3503793

Table 8

Statistical Moments of RM4 Distributions

Population	Mean	Variance	Std. Dev.
10L0	-.4188788	.0941331	.3068112
10L5	-.4258803	.0936967	.306099
10L10	-.423802	.0897187	.2995307
20L0	-.3667525	.0924979	.3041346
20L5	-.3749607	.1118555	.334448
20L10	-.3594583	.1141094	.3378008
30L0	-.31271	.109086	.3302818
30L5	-.3256386	.121957	.3492234
30L10	-.3049378	.111348	.3336884
10H0	-.4190774	.0940824	.3067285
10H5	-.425043	.0851494	.2918037
10H10	-.415741	.0794311	.281835
20H0	-.3662538	.111654	.3341467
20H5	-.3620137	.0943815	.3072156
20H10	-.36832	.1114834	.3338913
30H0	-.3221878	.1245809	.35296
30H5	-.3400995	.1128749	.3359686
30H10	-.3092027	.1261533	.3551807

Appendix D: Summary Statistics for Research Populations

Table 9

Summary Statistics for Population: 10L0

	EAC1	RM1
Mean	10552207.	-.3596454
Variance	1.004301e+14	.377067
Std. Dev.	10021483.	.614058
	EAC2	**RM2**
Mean	9693292.	-.4123724
Variance	2.789606e+13	.1024277
Std. Dev.	5281672.	.320043
	EAC3	**RM3**
Mean	9589969.	-.418999
Variance	2.591912e+13	.094054
Std. Dev.	5091082.	.3066823
	EAC4	**RM4**
Mean	9591994.	-.4188788
Variance	2.594234e+13	.0941331
Std. Dev.	5093362.	.3068112
	ACWP(60)	
Mean	16558777.	
Variance	1.693582e+12	
Std. Dev.	1301377.	

Table 10

Summary Statistics for Population: 10L5

	EAC1	RM1
Mean	10222382.	-.378712
Variance	1.917890e+14	.6658007
Std. Dev.	13848790.	.815966
	EAC2	**RM2**
Mean	9484483.	-.419743
Variance	2.765948e+13	.1021418
Std. Dev.	5259228.	.3195962
	EAC3	**RM3**
Mean	9351947.	-.427719
Variance	2.516910e+13	.0930635
Std. Dev.	5016882.	.305063
	EAC4	**RM4**
Mean	9382043.	-.4258803
Variance	2.534054e+13	.0936967
Std. Dev.	5033939.	.306099
	ACWP(60)	
Mean	16366193.	
Variance	1.483604e+12	
Std. Dev.	1218033.	

Table 11

Summary Statistics for Population: 10L10

	EAC1	RM1
Mean	10021643.	-.393657
Variance	1.571839e+14	.542814
Std. Dev.	12537300.	.736759
	EAC2	**RM2**
Mean	9529091.	-.419882
Variance	2.635388e+13	.096849
Std. Dev.	5133603.	.3112057
	EAC3	**RM3**
Mean	9404131.	-.4274625
Variance	2.410610e+13	.0884988
Std. Dev.	4909795.	.297489
	EAC4	**RM4**
Mean	9464296.	-.423802
Variance	2.443815e+13	.0897187
Std. Dev.	4943496.	.2995307
	ACWP(60)	
Mean	16451551.	
Variance	1.515712e+12	
Std. Dev.	1231143.	

Table 12

Summary Statistics for Population: 20L0

	EAC1	RM1
Mean	13815946.	-.2258958
Variance	1.379802e+15	5.26306
Std. Dev.	37145684.	2.294136

	EAC2	RM2
Mean	11628031.	-.36086
Variance	3.435702e+13	.1002212
Std. Dev.	5861486.	.3165773

	EAC3	RM3
Mean	11520133.	-.366683
Variance	3.175133e+13	.0925131
Std. Dev.	5634831.	.3041596

	EAC4	RM4
Mean	11519077.	-.3667525
Variance	3.175832e+13	.0924979
Std. Dev.	5635452.	.3041346

	ACWP(60)
Mean	18191970.
Variance	1.957210e+12
Std. Dev.	1399004.

Table 13

Summary Statistics for Population: 20L5

	EAC1	RM1
Mean	12113014.	-.3279834
Variance	6.668586e+14	1.97177
Std. Dev.	25823604.	1.404197

	EAC2	RM2
Mean	11279937.	-.367753
Variance	4.128770e+13	.127554
Std. Dev.	6425550.	.357147

	EAC3	RM3
Mean	11087327.	-.378269
Variance	3.572390e+13	.1106666
Std. Dev.	5976948.	.3326658

	EAC4	RM4
Mean	11146384.	-.3749607
Variance	3.610728e+13	.1118555
Std. Dev.	6008933.	.334448

	ACWP(60)
Mean	17848886.
Variance	1.769823e+12
Std. Dev.	1330347.

Table 14

Summary Statistics for Population: 20L10

	EAC1	RM1
Mean	12857628.	-.284222
Variance	2.633370e+14	.834229
Std. Dev.	16227658.	.913361

	EAC2	RM2
Mean	11533638.	-.3589566
Variance	4.092710e+13	.1269422
Std. Dev.	6397431.	.3562894

	EAC3	RM3
Mean	11413822.	-.3662427
Variance	3.663916e+13	.111564
Std. Dev.	6053029.	.334012

	EAC4	RM4
Mean	11535967.	-.3594583
Variance	3.747280e+13	.1141094
Std. Dev.	6121504.	.3378008

	ACWP(60)
Mean	18064804.
Variance	1.984660e+12
Std. Dev.	1408780.

Table 15

Summary Statistics for Population: 30L0

	EAC1	RM1
Mean	16645910.	-.1369596
Variance	2.687206e+15	8.68556
Std. Dev.	51838260.	2.947127
	EAC2	**RM2**
Mean	13674372.	-.3063355
Variance	4.855310e+13	.1207366
Std. Dev.	6968005.	.3474717
	EAC3	**RM3**
Mean	13546857.	-.3126217
Variance	4.391314e+13	.1091058
Std. Dev.	6626699.	.3303117
	EAC4	**RM4**
Mean	13545404.	-.31271
Variance	4.392570e+13	.109086
Std. Dev.	6627646.	.3302818
	ACWP(60)	
Mean	19709986.	
Variance	2.271806e+12	
Std. Dev.	1507251.	

Table 16

Summary Statistics for Population: 30L5

	EAC1	RM1
Mean	16524732.	-.1432385
Variance	2.759790e+15	8.85594
Std. Dev.	52533704.	2.975894

	EAC2	RM2
Mean	13362036.	-.3220447
Variance	5.388900e+13	.1353002
Std. Dev.	7340911.	.367832

	EAC3	RM3
Mean	13200820.	-.3301655
Variance	4.809944e+13	.1202938
Std. Dev.	6935376.	.346834

	EAC4	RM4
Mean	13290375.	-.3256386
Variance	4.878794e+13	.121957
Std. Dev.	6984836.	.3492234

	ACWP(60)
Mean	19714760.
Variance	2.293340e+12
Std. Dev.	1514378.

Table 17

Summary Statistics for Population: 30L10

	EAC1	RM1
Mean	16629110.	-.1376086
Variance	2.687208e+15	8.68554
Std. Dev.	51838284.	2.947124
	EAC2	**RM2**
Mean	13646116.	-.3075712
Variance	4.830540e+13	.1201053
Std. Dev.	6950208.	.346562
	EAC3	**RM3**
Mean	13516016.	-.3139995
Variance	4.365570e+13	.1084363
Std. Dev.	6607248.	.3292967
	EAC4	**RM4**
Mean	13694937.	-.3049378
Variance	4.485260e+13	.111348
Std. Dev.	6697207.	.3336884
	ACWP(60)	
Mean	19704774.	
Variance	2.280552e+12	
Std. Dev.	1510150.	

Table 18

Summary Statistics for Population: 10H0

	EAC1	RM1
Mean	311815616.	-.3901554
Variance	4.206544e+16	.1616249
Std. Dev.	205098592.	.402026

	EAC2	RM2
Mean	300046656.	-.413259
Variance	2.650512e+16	.1012668
Std. Dev.	162804000.	.3182245

	EAC3	RM3
Mean	297163000.	-.4191976
Variance	2.483380e+16	.0940038
Std. Dev.	157587408.	.3066003

	EAC4	RM4
Mean	297225792.	-.4190774
Variance	2.485590e+16	.0940824
Std. Dev.	157657568.	.3067285

	ACWP(60)
Mean	513188000.
Variance	1.443799e+15
Std. Dev.	37997352.

Table 19

Summary Statistics for Population: 10H5

	EAC1	RM1
Mean	312075456.	-.395343
Variance	5.103280e+16	.206625
Std. Dev.	225904432.	.45456

	EAC2	RM2
Mean	299169000.	-.4216004
Variance	2.443547e+16	.0895257
Std. Dev.	156318464.	.2992085

	EAC3	RM3
Mean	296437280.	-.4268747
Variance	2.314036e+16	.0845853
Std. Dev.	152119536.	.2908354

	EAC4	RM4
Mean	297388384.	-.425043
Variance	2.329998e+16	.0851494
Std. Dev.	152643296.	.2918037

	ACWP(60)
Mean	517600000.
Variance	1.411815e+15
Std. Dev.	37574124.

Table 20

Summary Statistics for Population: 10H10

	EAC1	RM1
Mean	314948480.	-.3894853
Variance	4.706270e+16	.1913368
Std. Dev.	216939440.	.4374206
	EAC2	**RM2**
Mean	302756800.	-.4143805
Variance	2.282570e+16	.0826822
Std. Dev.	151081776.	.287545
	EAC3	**RM3**
Mean	300169440.	-.4193546
Variance	2.168520e+16	.0784237
Std. Dev.	147259000.	.2800423
	EAC4	**RM4**
Mean	302044000.	-.415741
Variance	2.197182e+16	.0794311
Std. Dev.	148229000.	.281835
	ACWP(60)	
Mean	516755392.	
Variance	1.428110e+15	
Std. Dev.	37790332.	

Table 21

Summary Statistics for Population: 20H0

	EAC1	RM1
Mean	372786496.	-.3314503
Variance	8.399460e+16	.271928
Std. Dev.	289818240.	.521467

	EAC2	RM2
Mean	356882000.	-.360192
Variance	3.863110e+16	.1244955
Std. Dev.	196548000.	.352839

	EAC3	RM3
Mean	353678000.	-.3664585
Variance	3.510360e+16	.1115042
Std. Dev.	187359488.	.3339224

	EAC4	RM4
Mean	353794000.	-.3662538
Variance	3.515320e+16	.111654
Std. Dev.	187491840.	.3341467

	ACWP(60)
Mean	559863000.
Variance	1.688717e+15
Std. Dev.	41094000.

Table 22

Summary Statistics for Population: 20H5

	EAC1	RM1
Mean	379096000.	-.3258837
Variance	1.036054e+17	.359676
Std. Dev.	321878000.	.59973

	EAC2	RM2
Mean	361350304.	-.359221
Variance	3.319137e+16	.1012998
Std. Dev.	182185000.	.3182763

	EAC3	RM3
Mean	357890000.	-.365283
Variance	3.065988e+16	.0934018
Std. Dev.	175099600.	.305617

	EAC4	RM4
Mean	359740544.	-.3620137
Variance	3.099398e+16	.0943815
Std. Dev.	176051000.	.3072156

	ACWP(60)
Mean	563845000.
Variance	1.672740e+15
Std. Dev.	40899156.

Table 23

Summary Statistics for Population: 20H10

	EAC1	RM1
Mean	364959488.	-.343044
Variance	1.444690e+17	.4570483
Std. Dev.	380090656.	.6760535
	EAC2	**RM2**
Mean	351440000.	-.365342
Variance	3.880280e+16	.1245045
Std. Dev.	196984272.	.352852
	EAC3	**RM3**
Mean	345994000.	-.3749374
Variance	3.393490e+16	.1091143
Std. Dev.	184214272.	.3303246
	EAC4	**RM4**
Mean	349659000.	-.36832
Variance	3.467092e+16	.1114834
Std. Dev.	186201280.	.3338913
	ACWP(60)	
Mean	553945344.	
Variance	1.513225e+15	
Std. Dev.	38900192.	

Table 24

Summary Statistics for Population: 30H0

	EAC1	RM1
Mean	426566656.	-.29367
Variance	2.365435e+17	.64024
Std. Dev.	486357000.	.80015
	EAC2	**RM2**
Mean	414407712.	-.3109253
Variance	5.381430e+16	.146631
Std. Dev.	231979000.	.3829244
	EAC3	**RM3**
Mean	407460736.	-.3222148
Variance	4.561820e+16	.1245656
Std. Dev.	213584192.	.3529386
	EAC4	**RM4**
Mean	407476000.	-.3221878
Variance	4.561857e+16	.1245809
Std. Dev.	213585000.	.35296
	ACWP(60)	
Mean	601688000.	
Variance	1.770306e+15	
Std. Dev.	42075000.	

Table 25

Summary Statistics for Population: 30H5

	EAC1	RM1
Mean	416611520.	-.297774
Variance	1.871683e+17	.565738
Std. Dev.	432629504.	.7521555

	EAC2	RM2
Mean	394192512.	-.336999
Variance	4.644060e+16	.1256891
Std. Dev.	215500800.	.3545266

	EAC3	RM3
Mean	389761000.	-.344216
Variance	4.108870e+16	.1113792
Std. Dev.	202703472.	.333735

	EAC4	RM4
Mean	392229000.	-.3400995
Variance	4.167227e+16	.1128749
Std. Dev.	204139000.	.3359686

	ACWP(60)
Mean	593819000.
Variance	2.124235e+15
Std. Dev.	46089416.

Table 26

Summary Statistics for Population: 30H10

	EAC1	RM1
Mean	428850560.	-.29059
Variance	2.361100e+17	.638918
Std. Dev.	485911520.	.799324

	EAC2	RM2
Mean	416608000.	-.3078258
Variance	5.269840e+16	.1438957
Std. Dev.	229561312.	.379336

	EAC3	RM3
Mean	410118400.	-.3183693
Variance	4.486460e+16	.1227657
Std. Dev.	211812592.	.3503793

	EAC4	RM4
Mean	415633000.	-.3092027
Variance	4.609816e+16	.1261533
Std. Dev.	214704800.	.3551807

	ACWP(60)
Mean	602419000.
Variance	1.757942e+15
Std. Dev.	41927812.

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VITA

Captain Darren E. Morgan was born on 24 August 1960 in Frederick, Maryland. He graduated from high school in Walkersville, Maryland, in 1978 and attended the University of Maryland, from which he received the degree of Bachelor of Science in Aerospace Engineering in May 1982. Upon graduation, he received a commission in the USAF through the Officer Training School program. He began his active duty commissioned service in August 1982 as a Ballistic Missile Facilities Analyst at the Foreign Technology Division (FTD), Wright-Patterson AFB, Ohio. He then transferred to the Ballistic and Space Preliminary Design Branch of FTD where he worked as an aerospace engineer until entering the School of Systems and Logistics, Air Force Institute of Technology, in May 1986.

Permanent Address: 104 Liberty Road
Woodsboro, Maryland 21798

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This thesis examined the robustness of methods used to compute estimates at completion of contract costs. The four techniques examined were a subset of those used by the Cost Performance Report Analysis computer program to derive estimates at completion.

Monte Carlo simulation methods were used to generate the required data values for 18 simulated populations representing a variety of possible cost and schedule overrun scenarios. A statistical evaluation of the robustness of the four estimate at completion techniques was performed using samples from each of the 18 simulated populations.

The results of this analysis indicate that, for practical purposes, none of the selected estimate at completion techniques are robust for the cost and schedule overrun scenarios that were investigated. The tendency of each of the estimate at completion models was to underestimate the final contract cost. The estimate at completion models incorporating mathematical smoothing techniques (i.e. weightings or moving averages) provided relatively stable results across all of the populations; however, they were unable to consistently predict a contract's completion cost within 30 percent of the actual value. Of the four methods investigated, the method based upon the Cost Performance Index for a single month was the most unreliable predictor of the final contract cost.